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Ontologies for Industry 4.0

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Abstract

The current fourth industrial revolution, or 'Industry 4.0' (I4.0), is driven by digital data, connectivity, and cyber systems, and it has the potential to create impressive/new business opportunities. With the arrival of I4.0, the scenario of various intelligent systems interacting reliably and securely with each other becomes a reality which technical systems need to address. One major aspect of I4.0 is to adopt a coherent approach for the semantic communication in between multiple intelligent systems, which include human and artificial (software or hardware) agents. For this purpose, ontologies can provide the solution by formalizing the smart manufacturing knowledge in an interoperable way. Hence, this paper presents the few existing ontologies for I4.0, along with the current state of the standardization effort in the factory 4.0 domain and examples of real-world scenarios for I4.0.

1 Introduction

1.1 What is Industry 4.0?

Industry 4.0 (I4.0) is a term coined to represent the fourth industrial revolution based on the latest technological advances. While it represents an application of the concept of *Cyber-Physical System (CPS)* (Veera Ragavan & Shanmugavel, 2016), which is understood as its core (Lee *et al.*, 2015), it goes far beyond CPS, involving advanced data communication systems (Wollschlaeger *et al.*, 2017), embedded intelligence (Wang *et al.*, 2016), and data semantic standardization (Fiorini *et al.*, 2017).

I4.0, which was initiated at the beginning of this decade by national programs (Haupert *et al.*, 2014) called *Smart Manufacturing* Leadership Coalition[1] in the US and *Industrie 4.0*[2] in Germany, has already proven to be a no-way-back trend that has the potential to take today's Industry to a higher level of efficiency, performance, and productivity, as started to be used by companies such as ABB and Siemens (Drath & Horch, 2014).

Indeed, I4.0 scenarios can present, for example, physical objects manipulated by means of their virtual representations which by their turn provide services that, at the end, support applications for highly detailed product customization, precise and timely accurate logistics supply chains, and efficient product delivery. Everything related to the production could be represented in the cyberspace, from the smallest and least significant raw material or component up to the complete product and all the machinery involved in its production (Rosen *et al.*, 2015). This setup relies on fast and efficient data transmission, supported by wireless communication technologies such as 5G (Rappaport *et al.*, 2013), in which product subsystems could decide autonomously their best and most optimized production process, concurrently exchanging data with other components and elements of the industrial environment.

Hence, in an I4.0 scenario, the manufacturing process is the main activity and, among several equipments, autonomous robots are extensively used toward manufacturing performance and revenue improvements (Kattepur *et al.*, 2018; Zhang *et al.*, 2019). This helps to explain why power consumption related to motors represents two tier of the electrical power consumed by the industry sector (Saidur, 2010). Combined with currently available techniques of data analysis and cognition, this creates new possibilities of interoperability, modularity, distributed processing, and integration in real time with other systems for industrial processes. In fact, those possibilities constitute the core concept of I4.0 (Hermann *et al.*, 2016).

1.2 Technologies for Industry 4.0

I4.0 or *smart factory* (Kannengiesser & Muller, 2013) is based on new and radically changed processes in manufacturing industry. It represents a number of contemporary automation, data exchange, and manufacturing technologies (Hermann *et al.*, 2016), such as virtual enterprise (Smirnov *et al.*, 2010), cloud manufacturing (Xie *et al.*, 2017), *Internet of Things* (IoT), also named by Cisco as *Internet of Everything* (Zheng *et al.*, 2014), and its emerging concepts *Industrial Internet of Things* (IIoT) (Civerchia *et al.*, 2017) or *Industrial Internet* as used in the US by General Electric (GE) to represent the realization of IoT for industrial applications.

In particular, data are gathered from suppliers, customers, and the plant/factory itself and evaluated before being linked up with real production. The latter is increasingly using new technologies such as data analytics, smart sensors, cloud computing, and next-generation robots (Haidegger *et al.*, 2019). This results in flexible and adaptive production processes that are fine-tuned, adjusted, or set up differently in real time (Hermann *et al.*, 2014).

Traditional industry relies on ISA-95, a well-defined five-layer automation architecture. The machine level (i.e. field devices such as sensors and actuators) is at the lowest level and sends/receives data via digital or analog signals to the control level, for example, the Programmable Logic Controller. Supervisor Control and Data Acquisition systems in the cell level perform (remote) control tasks. Manufacturing Execution Systems in the process control level allow users to perform complex tasks such as production scheduling. Top-level Enterprise Resource Planning or factory operation management level allows the management reporting and shares manufacturing data such as the order status with other systems (Wollschlaeger *et al.*, 2017).

The fourth industrial revolution I4.0 represents a new paradigm shift from the *centralized* to the *decentralized* industry, relying on the cyber-physical-based automation, where sensors send data directly to the cloud and where services such as monitoring, control, and optimization automatically subscribe to the necessary data in real time. Hence, I4.0 involves flexible production networks that require horizontal

[1] http://smartmanufacturingcoalition.org/http://smartmanufacturingcoalition.org/.
[2] http://www.hightech-strategie.de/de/59.phphttp://www.hightech-strategie.de/de/59.php.

integration across the company, while any production-related information exchanged in the network must be vertically forwarded to the corresponding service endpoint of the local production system (Wally *et al.*, 2017). The ultimate goal of this emerging technology is to improve the work conditions and to increase productivity, speed, precision, repeatability, reliability, flexibility, and competitiveness. In the coming years, these technologies will be seen as a viable alternative to the current manufacturing processes, and will enable mass customization, faster production, better quality, increased productivity, and improved decision-making (Da Xu *et al.*, 2014).

It is worth noting that mass customization can allow the production of small lots at reasonable cost, due to the ability to rapidly configure machines in order to adapt to the customer-supplied specifications and additive manufacturing (Wang *et al.*, 2016). On the other hand, data-driven supply chains can speed up the manufacturing process by an estimated 120% in terms of time needed to deliver orders and by 70% in time to get products to market (Davies, 2015). Thence, I4.0 technologies aim to improve the product quality and dramatically reduce the costs of scrapping or reworking defective products. Predictive maintenance and self-healing technologies in I4.0 intend to enable plants/factories to keep running in order to guarantee the productivity. I4.0 technologies could allow individuals and companies to share access to products, services, and experiences, enabling ‘sharing economy’ as a new business model. With access to factory and cross-market data, decision-makers can predict, response, and adapt to factory needs and market trends in an accurate and timely manner. Some estimates indicate that smart factory technology will have global market size of USD 62.98 billion by 2019 and USD 74.80 billion by 2022 (Markets and Markets, 2016).

1.3 Challenges of Industry 4.0

I4.0 is opening the door for a new industrial revolution. In order to understand the contributions and challenges of I4.0, and how it will influence life at different levels of development, it is important to keep in mind how revolutionary industrial changes took place and their contribution to the evolution of technology since the first industrial revolution. Britain was the birthplace of the first technological revolution which emerged in the late 18th century with the invention of the steam engine and the introduction of new mechanical production facilities. The second industrial revolution encompassed at the end of the 19th century the development of electrical, chemical, and motor-vehicle engineering sectors, while the third industrial revolution came up with developments in the electronic and aerospace sectors, leading to the omnipresence of Information Technology systems and production automation (MacDonald, 2016).

The fourth industrial revolution is initiating the use of CPS (Lee *et al.*, 2015) and is focused on the development of a new generation of intelligent and integrated technologies for smart manufacturing (Ivezic & Ljubicic, 2016), seeking to optimize its planning and usage across different industrial domains such as oil and gas industry (Du *et al.*, 2010), (Guo & Wu, 2012), mining (Xue & Chang, 2012), energy (Teixeira *et al.*, 2017), steel production (Dobrev *et al.*, 2008), construction (Sorli *et al.*, 2006), aviation (Hoppe *et al.*, 2017; Lehmann *et al.*, 2018), automotive industry (Phutthisathian *et al.*, 2013), electronic industry (Liu *et al.*, 2005a), chemical industry (Natarajan *et al.*, 2011), and process engineering (Wiesner *et al.*, 2010). In addition, the concept of virtual production is considered to be the key factor for modeling production aiming for zero defects (MacDonald, 2016).

Hence, the driving force behind the development of I4.0 is the rapidly increasing digitization of the economy and society, in the sectors of agriculture (Jayarathna & Hettige, 2013), production (Meridou *et al.*, 2015), and services, for example, banking (Atkinson *et al.*, 2006), telecom (Agrawal *et al.*, 2008), tourism (Fang *et al.*, 2016), or insurance (Koetter *et al.*, 2019).

I4.0 integrates also the state of the art of communication technologies such as cloud (Xu, 2012; Xie *et al.*, 2017), IoT (Cagnin *et al.*, 2018; Wan *et al.*, 2018a) with the new trends of evolved intelligent industrial technologies, such as new-generation intelligent agents (Kannengiesser & Muller, 2013), Internet of Robotics Things (Ray, 2016), Augmented Reality. and Virtual Realty (Flatt *et al.*, 2015; Ivaschenko *et al.*, 2018).

Despite the benefits and advances promised by I4.0, the players in this arena have a wide range of challenges to cope with, from human–robot interaction (Jost *et al.*, 2017; Calzado *et al.*, 2018) to data analysis (Xu & Hua, 2017; Li & Niggemann, 2018). On the other hand, wireless communication are also an important factor in I4.0. With 5G networks still under development (Nordrum & Clark, 2017), other wireless technologies are being adopted in the meantime, leading to the need for networks' coexistence solutions (de Moura Leite *et al.*, 2017). Furthermore, I4.0 requires the understanding of data heterogeneity in the context of CPSs integration (Jirkovsky *et al.*, 2017; Matzler & Wollschlaeger, 2017) as well as the interoperability (Salminen & Pillai, 2007; Nilsson & Sandin, 2018) within the agent-based ecosystem (Kao & Chen, 2010) for unambiguous communication (Zhang *et al.*, 2018), efficient collaboration (Olszewska, 2017), and cooperation (Hildebrandt *et al.*, 2017). Thence, information and data used for smart manufacturing should follow a semantic standard (Macia-Perez *et al.*, 2009) throughout the whole industrial environment.

In particular, ontologies are a powerful solution to capture (Liandong & Qifeng, 2009) and to share the common knowledge (Hoppe *et al.*, 2017) among the distributed partners of the I4.0 technology, leading, for example, to Context-as-a-Service platforms (Hassani *et al.*, 2018). Indeed, ontologies aim to make domain knowledge explicit and remove ambiguities, enable machines to reason, and facilitate knowledge sharing between machines and humans (Persson & Wallin, 2017) and in between machines (Olszewska & Allison, 2018). Moreover, ontologies for the I4.0 are required to be business focused, that is promoting cooperation with customers and partners (Persson & Wallin, 2017) and, on the other hand, meet ontological, autonomous robotic requirements (Bayat *et al.*, 2016). Furthermore, ontologies need to analyze and reuse domain knowledge by using present ontologies (Persson & Wallin, 2017).

Focusing on the abovementioned characteristics, this paper approaches the I4.0 theme through an ontological perspective, meeting the mandatory requirement of consistent and standardized data semantics. The goal of our work is to contribute toward the effort of unambiguously representing domain knowledge in order to assist I4.0 practitioners in the development of coherent and efficient systems. The contribution proposed in this paper is an ontological perspective of the I4.0 domain, with a highlight on the autonomous robotic facet of I4.0.

The rest of the paper is structured as follows. Section 2 presents existing ontologies for the I4.0 domain, along with a literature overview about relevant standardization efforts in the smart manufacturing field, with an emphasis on its autonomous robotic aspect. Section 3 describes real-world case studies providing potential applications for the use of I4.0 ontologies, while Section 4 concludes the work with reflections and future directions.

2 Industry 4.0 ontologies

2.1 *Industry 4.0 ontological frameworks*

Ontologies consist in a formal conceptualization of the knowledge representation and provide the definitions of the concepts and relations capturing the knowledge of a domain in an interoperable way (Wang *et al.*, 2010).

The domain of *I4.0* or *Factory 4.0* or *Smart Manufacturing* consists of concepts related, on the one hand, to business services (Wally *et al.*, 2017), encompassing automatization of the project management (Martin-Montes *et al.*, 2017), organizational management (Izhar and Apduhan, 2017), customer satisfaction management (Kim and Lee, 2013; Daly *et al.*, 2015), risk management (Atkinson *et al.*, 2006), and virtualization of operations (Jiang *et al.*, Smirnov *et al.*, 2004; 2010), such as billing (Agrawal *et al.*, 2008), ticketing (Vukmirovic *et al.*, 2006), generation of recommendations (Lorenzi *et al.*, 2011), and decision-making aids (Koetter *et al.*, 2019).

On the other hand, production services (Wally *et al.*, 2017) involve abstractions of manufacturing processes (Brodsky *et al.*, 2016; Tang *et al.*, 2018), such as production management (Yusupova *et al.*), product compliance (Disi & Zualkernan, 2009), resource reconfiguration (Wan *et al.*, 2018b), decision support (Arena *et al.*, 2017), and intelligence-based automatization of chain processes (Muller *et al.*, 2018), such as assembly (Merdan *et al.*, 2008; Cecil *et al.*, 2018) and/or diassembly (Koppensteiner *et al.*, 2011), packaging (Wan *et al.*, 2019), shipping (Phutthisathian *et al.*, 2013) as well as system diagnosis

(Bunte *et al.*, 2016), product control (Bunte *et al.*, 2016), safety control (Akbari *et al.*, 2010), and security inspection (Mozzaquatro *et al.*, 2016).

For this purpose, in the last decade, ontologies have been developed for one specific industrial domain such as aviation (Keller, 2016), aeropsace (Kossmann *et al.*, 2009), construction (Liao *et al.*, 2009), steel production (Dobrev *et al.*, 2008), chemical engineering (Vinoth & Sankar, 2016; Feng *et al.*, 2018), oil industry (Du *et al.*, 2010; Guo & Wu, 2012), energy (Santos *et al.*, 2018), and electronics (Liu *et al.*, 2005a). Other ontologies have been used for one specific manufacturing process such as packaging (Liu *et al.*, 2005b), process engineering (Wiesner *et al.*, 2010), process compliance (Disi & Zualkernan, 2009), risk management (Atkinson *et al.*, 2006), safety management (Hooi *et al.*, 2012), customer feedback analysis (Kim and Lee, 2013; Daly *et al.*, 2015), organizational management (Grangel-Gonzalez *et al.*, 2016; Izhar and Apduhan, 2017), project management (Cheah *et al.*, 2011), product development (Zhang *et al.*, 2017), maintenance (Haupert *et al.*, 2014), resource reconfiguration (Wan *et al.*, 2018b), and production scheduling (Kourtis *et al.*, 2019). Ontologies have also been focused on one service, for example, ticketing (Vukmirovic *et al.*, 2006), or on one manufacturing concept, for example, information flow (Bildstein and Feng, 2018), information security (Mozzaquatro *et al.*, 2016), and data integration (Yusupova *et al.*).

More recently, two ontological frameworks tending to cover the wider domain of smart manufacturing have been proposed. Hence, Cheng *et al.* (2016) provided a model of the production line using a combination of five ontologies, namely, device ontology (with concepts such as *Machine*), process ontology (with a taxonomy of the different *Operations* performed by the technical equipment), parameter ontology (with concepts such as *Quality of Service*), product ontology (with the product information), and the base ontology (integrated the four others and defining the concept *Order*). On the other hand, Engel *et al.* (2018) proposed a three-layer ontology for batch process plants. The first layer, or application layer, contains the operations; the second layer, or domain layer, the architecture, while the third layer, or upper layer, refers to an upper ontological model describing general system characteristics and relations.

These ontologies have been proven to bring some advances in the field, but they have a limited scope and/or a basic vocabulary. Hence, the effort to standardize the whole domain is a huge enterprise, and some current results of this standardization work are reported in Section 2.2.

2.2 Industry 4.0 ontological standards

2.2.1 Ontological standard effort

As I4.0 relies heavily on robotic agents which have to evolve and perform the main operations in smart manufacturing environment and which are solicited to communicate with human operators, customers, or with diverse distributed partners, the standardization of knowledge representation is a key element facing I4.0 development and is required to be addressed quickly and efficiently to avoid accumulated difficulties at later stages of the development. Hence, the ontological standardization effort for I4.0 builds upon the IEEE 1872-2015 Standard Ontologies for Robotics and Automation (IEEE-SA, 2015), which establishes a series of ontologies about the Robotics and Automation (R&A) domain (Fiorini *et al.*, 2017) that can be extended to the I4.0. by incorporating new I4.0-specific ontological concepts, as described in the next paragraphs.

CORA Ontology. The Core Ontology for Robotics and Automation (CORA) (Prestes *et al.*, 2013) developed within the IEEE 1872-2015 Standard Ontologies for Robotics and Automation (IEEE-SA, 2015) is a core ontology for robotics. A core ontology specifies concepts that are general in a whole domain such as Robotics. In the case of CORA, it defines concepts such as *Robot*, *Robot Group*, and *Robotic System*. Its role is to serve as basis for other more specialized ontologies in R&A, currently developed within IEEE P1872.1 and P1872.2 standardization efforts, and focused on Robot Task Representation and Autonomous Robotics, respectively. Moreover, it determines a set of basic ontological commitments, which should help robot developers and other ontologists to create models about robots (Bayat *et al.*, 2016).

ROA Ontology. The Ontology for Autonomous Robotics (ROA) (Olszewska *et al.*, 2017) defines robotic notions identified as fundamental (Ivezic & Ljubicic, 2016) for Autonomous Robotics. Hence,

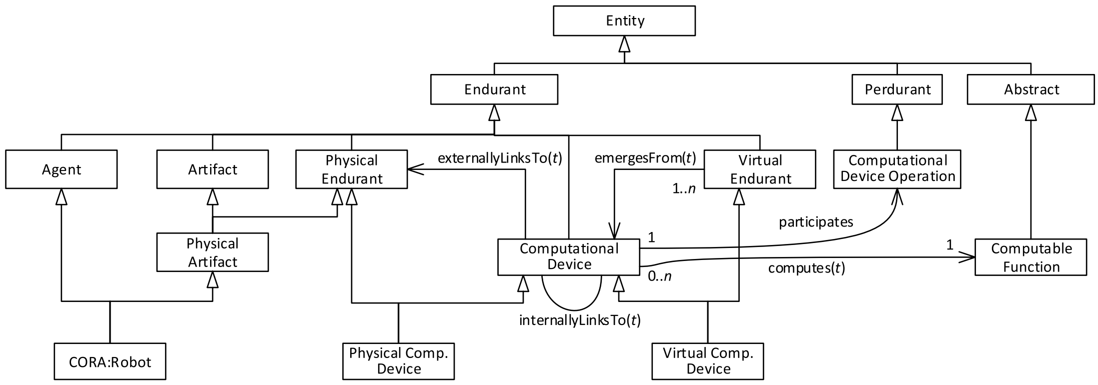

Figure 1 Ontological concepts of robotic hardware and software as conceived in ORArch and O4I4 ontologies

ROA provides the definitions of behavior, function, goal, and task concepts and reuses ontologies such as the Suggested Upper Merged Ontology (SUMO) upper ontology, the CORA core ontology, and specialized ontologies such as the Spatio-Temporal Visual Ontology (Olszewska, 2011).

ORArch Ontology. The Ontology for Robotic Architecture (ORArch) elaborates notions related to hardware and software, as well as how these can be represented together in mixed architecture descriptions. Moreover, ROA aims to allow one to describe multiple architectural viewpoints of the same robot, which combines hardware and software devices.

Figure 1 depicts the main concepts of this ontology. The top concepts are part of the top-level ontology. The ontology divides the reality as endurants, perdurants, and abstracts. Endurant and perdurants are entities that are situated in time, while abstract entities are not. Perdurants have temporal parts like processes and events, while endurants have no temporal parts such as physical and social objects. Abstract entities are formal entities, for example, the logical and mathematical entities.

The main aspect of this ontology is the separation between physical and virtual endurants. Physical endurants are objects of everyday life. Virtual endurants emerge from computational devices in operation. Computation devices are entities that perform the computation of a computable function. Examples of virtual endurants are typical entities related to running software (e.g. processes, threads, components, objects, and procedures) and other virtual-reality entities.

The ontology also imports the notion of *Robot* from CORA. We introduced some concepts (and axiomatization) such as *Artifact* to align its meaning with CORA/SUMO.

The concepts dealing with the architecture are shown in Figure 2. ORArch includes descriptions and situations (DnS) ontology to describe the robot architecture. DnS allows the representation of descriptions without the need for second-order languages. It has two main concepts, namely *Description* and *Situation*. A *Situation* is an entity similar to a collection which aggregates (i.e. is setting for) some entities that should be taken into consideration together for a given reason. An example of situations is the plant or a navigation context for a robot. A situation satisfies one or more descriptions. A *Description* defines concepts and roles that classify elements of a situation. A description of a plant would define the concepts of type A product and type B product, which classify instances of products. A description of a robot context defines concepts such as objective and obstacle, which classify object and regions in different situations. It is important to note that instances of a concept are distinct of the concepts that form the ontology itself. Let's consider, for example, the concept *Mobile Robot*. It might appear in the ontology as a subclass of *CORA:Robot* and also an instance of *RobotType*. Both these entities are treated as different. In ORArch, we consider that the notion of robot architecture has two sides. It can refer to a selection of components in a given, constructed robot, and it can also refer to an architectural model or description of an architecture that might be present in different robots. These two notions are captured by the concepts *(Robot Architecture) Viewpoint* and *(Robot Architecture) Description* in Figure 2.

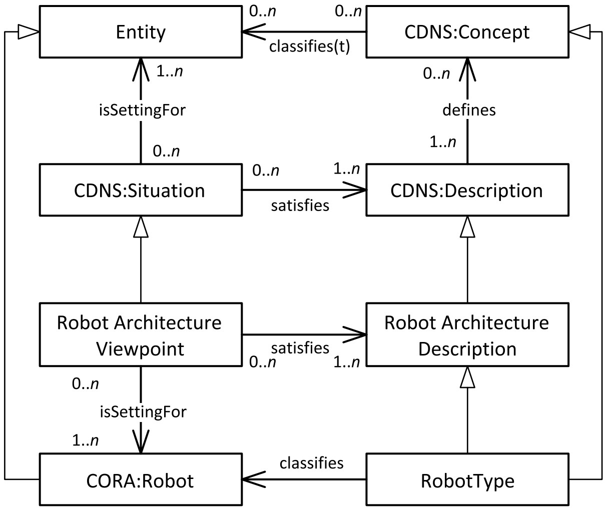

Figure 2 Concepts about robot architecture viewpoint and description in ORArch

O4I4 Ontology. The Ontology for Industry 4.0 (O4I4) is dedicated to capture the I4.0-specific domain concepts, while reusing CORA, ROA, and ORArch ontologies for the robotic facet of smart manufacturing. It is worth noting that CORA used SUMO as the upper ontology. However, in the light of the requirements of the suite of standardization ontologies (Fiorini *et al.*, 2017), it is planned that SUMO becomes optional as a top-level ontology in P1872.2. One reason is that some users of IEEE 1872 (IEEE-SA, 2015) voiced their desire to use CORA with other top-level ontologies. On the one hand, SUMO is too big and complex for customizable projects. Hence, with O4I4 which aims to be a business-focused ontology, we began defining a minimal top-level ontology to support our development. Such top-level ontology is also optional, but also should be easier to map to other top-level ontologies, if need be.

The new I4.0-specific concepts appear in Figure 1 and their definition is as follows:

- *Computable Function* is an abstract entity representing a given computable function with defined input(s) and output(s).
- *Computational Device Operation* is a perdurant denoting the functioning of a computational device.

Moreover, in the O4I4 ontological standard, the concept of *Computable Service* is defined as a *Computational Device Operation* which captures the notion of the process in which an agent has to compute an external request (with a possible input) and to deliver a result (output). However, a computable service can only exist if the agent has the *Capability* of performing that service which includes the availability of a *Physical Computational Device*. Thence, the computable service exists from the moment in which the requester starts being served and not from the moment in which the agent is requested. It is worth noting that a computable service is a sort of service from a computational science point of view. Other classes of services could be developed in the future to cover notions related to robotic service, etc.

2.2.2 Ontological standard roadmap

To sum up, the standard design using formal models consists of (i) the development of standard vocabularies for robotic concepts; (ii) the development of a functional ontology for Autonomous Robotics; (iii) the validation of relationship using functions as a basis for relationship checking; and (iv) the use of developed vocabularies and ontologies for I4.0 applications.

The benefits of such design are twofold. On the one hand, academics can discuss concepts unambiguously on the topic which will pave way for further research and investigation on the topic (Bermejo-Alonso *et al.*, 2018). On the other hand, Industry practitioners can use these ontologies to conceptualize implementation scenarios (Olszewska *et al.*, 2019). Indeed, as every scenario considered within the framework of the I4.0 includes different entities which communicate and cooperate with each

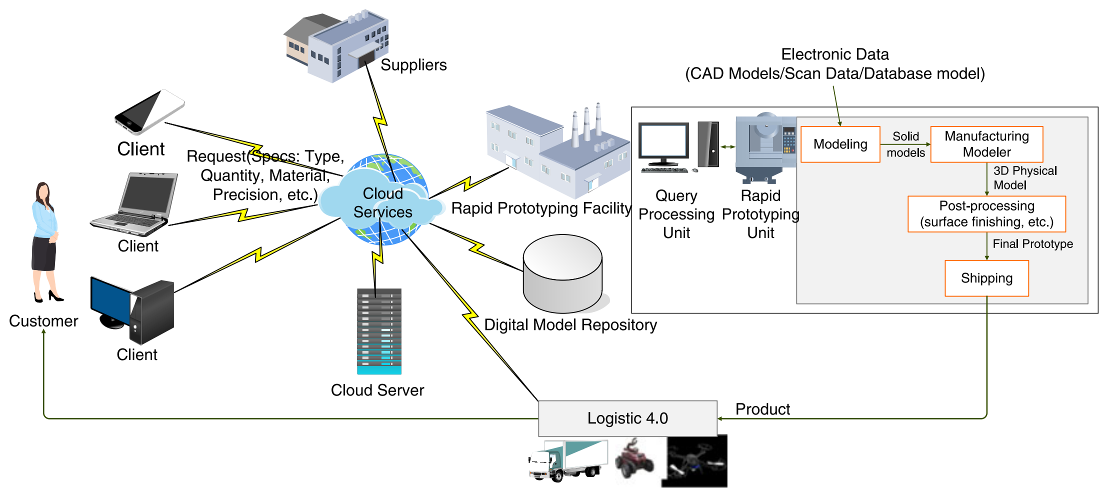

Figure 3 Overview of the smart-rapid prototyping scenario

other, the main role of the presented ontological standard is to facilitate that exchange, as exemplified in Section 3.

3 Industry 4.0 scenarios

3.1 Smart-rapid prototyping scenario

In I4.0, 3D printing manufacturing is a key-technology enabler for smart factories. This technology is also known as rapid prototyping, digital fabrication, solid imaging, free-form fabrication, layer-based manufacturing, and laser prototyping. The process involves building prototypes or working models in a relatively short time to help the creation and the testing of various design features, ideas, concepts, functionalities, and in certain instances, the outcome and performance (Bagaria *et al.*, 2011). Nowadays, there is a growing need and expectation of more rapid bespoke production, in order to both deliver the rapid prototyping of more products and variants and to support specialist products and obsolete parts globally and locally. Rapid prototyping provides a viable way to quickly and cost effectively deliver components or complete products as well as decrease the holding and transporting stock (and obsolescence concerns) (Burke *et al.*, 2015).

In a smart-rapid prototyping scenario (Figure 3), a customer with a predefined profile accesses a Web service to send a query to the manufacturing facility. This query contains the specifications of the part to be manufactured by the smart-rapid prototyping facility including the digital model uploaded by the customer or selected from an online digital model repository, as well as the material, the color, and the number of required units. The customer's query is then parsed and directed to the rapid prototyping unit that generates or retrieves the solid model to be sent to the manufacturing modeler that creates the 3D physical model. Post-processing such as surface finishing is then applied to create the final prototype that is shipped to the customer via logistic 4.0 technologies such as connected trucks, autonomous ground/aerial vehicles. Moreover, the customer is able to track all the manufacturing steps from the receipt of the request to the delivery of the final prototype.

In this scenario, the exchange of information and resources among those entities becomes crucial to obtain a good performance of the system as a whole, and the ontological approach can facilitate this exchange of information through the use of the defined concepts like *Computable Function*, *Computational Device Operation*, and *Computable Service*. Furthermore, the use of O4I4 ontology contributes toward the uniformization of the attributes required within the process as well as their unambiguous interpretation by both the machines and the customer.

3.2 UAV's good delivery scenario

Another crucial element of I4.0 is the efficient good delivery. Thence, let's consider a scenario where an operator has to supervise goods' delivery via unmanned aerial vehicles (UAVs), assigning different UAVs to different delivery tasks. These UAVs have a fault detection system that can detect and inform the operator about degradation in performance. Based on that information, the operator has to infer if that particular drone can be kept in operation or it has to be brought back for maintenance. This kind of reasoning requires considerable amount of expertise, since it has to be precise and relatively quick. This might hinder the adoption of UAVs by non-specialized business, such as pizza delivery, for instance.

An ontological approach can help this type of human–robot systems in many aspects, and as a consequence, enables the business to grow. For example, the ROA ontology (Olszewska *et al.*, 2017) (described in Section 2.2) provides formal concepts such as *Task*, *Function*, and *Behavior* as well as spatio-temporal relations. In this scenario, this can aid, on the one hand, the robot to unambiguously communicate the status information about itself to a human operator and, on the other hand, this can aid the operator's decision-making. Indeed, through automated reasoning, the robotic system can display more meaningful and simpler information. For instance, let's consider that the malfunctioning UAV was designed with the function of delivering packages in confined places, such as corridors. As its motors degrade, it starts to display different behaviors, such as small, but sudden changes in its trajectory, which it is able to correct if enough space is available. In a non-intelligent system, the operator alone has to check if the displayed behavior is compatible with the designed function of the robot and decide about grounding it or not. Depending on the knowledge or workload of the operator, these can become expansive and/or dangerous operations. With an ontology representing the robot architecture, the system can autonomously classify the erratic movements and infer whether they fulfill the designed function of delivering pizza. This system can then inform the user directly of this fact, unloading the operator of having to decode low-level warning signals and decide the best course of action, which improves the operator's general situation awareness.

4 Conclusions

The use of robotic agents in context of I4.0 has triggered, among others, the need to develop an interoperable communication model to interconnect them efficiently. Hence, an unambiguous, semantic-based knowledge representation of concepts for smart manufacturing domain is required to ensure a coherent and effective human–robot collaboration. For this purpose, ontologies have been identified as a possible solution for the representation of the vocabulary describing the key concepts related to this fourth industrial revolution. Thence, this paper presents the current state of ontologies for I4.0 and reviews both existing ontological frameworks and ontological standardization efforts in that field. Moreover, illustrative I4.0 scenarios have been provided to raise the awareness of practitioners about the potential of using ontologies for I4.0.

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References

Agrawal, H., Chafle, G., Goyal, S., Mittal, S. & Mukherjea, S. 2008. An enhanced extract-transform-load system for migrating data in telecom billing. In *IEEE International Conference on Data Engineering*, 1277–1286.

Akbari, A., Setayeshmehr, A., Borsi, H., Gockenbach, E. & Fofana, I. 2010. Intelligent agent-based system using dissolved gas analysis to detect incipient faults in power transformers. *IEEE Electrical Insulation Magazine* **26**(6), 27–40.

Arena, D., Kiritsis, D., Ziogou, C. & Voutetakis, S. 2017. Semantics-driven knowledge representation for decision support and status awareness at process plant floors. In *IEEE International Conference on Engineering, Technology and Innovation*, 902–908.

Atkinson, C., Cuske, C. & Dickopp, T. 2006. Concepts for an ontology-centric technology risk management architecture in the banking industry. In *IEEE International Enterprise Distributed Object Computing Conference Workshops*, 21–21.

Bagaria, V., Rasalkar, D., Ilyas, J. & Bagaria, S. 2011. Medical applications of rapid prototyping - A new horizon. *InTech Open Access*.

Bayat, B., Bermejo-Alonso, J., Carbonera, J. L., Facchinetti, T., Fiorini, S., Goncalves, P., Jorge, V. A. M., Habib, M., Khamis, A., Melo, K., Nguyen, B., Olszewska, J. I., Paull, L., Prestes, E., Ragavan, V., Saeedi, S., Sanz, R., Seto, M., Spencer, B., Vosughi, A. & Li, H. 2016. Requirements for building an ontology for autonomous robots. *Industrial Robot: An International Journal* **43**(5), 469–480.

Bermejo-Alonso, J., Chibani, A., Goncalves, P., Li, H., Jordan, S., Olivares, A., Olszewska, J. I., Prestes, E., Fiorini, S. R. & Sanz, R. 2018. Collaboratively working towards ontology-based standards for robotics and automation. In *IEEE International Conference on Intelligent Robots and Systems (IROS)*.

Bildstein, A. & Feng, J. 2018. Using ontologies for representing classifications of an information flow based matching framework for smart manufacturing. In *IEEE International Conference on Engineering, Technology and Innovation*, 1–8.

Brodsky, A., Krishnamoorthy, M., Bernstein, W. Z. and Nachawati, M. O. 2016. A system and architecture for reusable abstractions of manufacturing processes. In *IEEE International Conference on Big Data*, 2004–2013.

Bunte, A., Diedrich, A. & Niggemann, O. 2016. Integrating semantics for diagnosis of manufacturing systems. In *IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 1–8.

Burke, R., Mussomeli, A., Laaper, S., Hartigan, M. & Sniderman, B. 2015. *Smart Factory: Connecting Data, Machines, People and Processes. Technical report. Deloitte Insights*.

Cagnin, R. L., Guilherme, I. R., Queiroz, J., Paulo, B. & Neto, M. F. O. 2018. A multi-agent system approach for management of industrial IoT devices in manufacturing processes. In *IEEE International Conference on Industrial Informatics (INDIN)*, 31–36.

Calzado, J., Lindsay, A., Chen, C., Samuels, G. & Olszewska, J. I. 2018. SAMI: interactive, multi-sense robot architecture. In *IEEE International Symposium on Intelligent Engineering Systems*, 317–322.

Cecil, J., Albuhamood, S. & Cecil-Xavier, A. 2018. An Industry 4.0 cyber-physical framework for micro devices assembly. In *IEEE International Conference on Automation Science and Engineering*, 427–432.

Cheah, Y.-N., Khoh, S. B. & Ooi, G. B. 2011. An ontological approach for program management lessons learned: case study at motorola penang design centre. In *IEEE International Conference on Industrial Engineering and Engineering Management*, 1612–1616.

Cheng, H., Zeng, P., Xue, L., Shi, Z., Wang, P. & Yu, H. 2016. Manufacturing ontology development based on Industry 4.0 demonstration production line. In *IEEE International Conference on Trustworthy Systems and their Applications*, 42–47.

Civerchia, F., Bocchino, S., Salvadori, C., Rossi, E., Maggiani, L. & Petracca, M. 2017. Industrial Internet of Things monitoring solution for advanced predictive maintenance applications. *Journal of Industrial Information Integration* **7** (Supplement C), 4–12.

Da Xu, L., He, W. & Li, S. 2014. Internet of Things in industries: a survey. *IEEE Transactions on Industrial Informatics* **10**(4), 2233–2243.

Daly, M., Grow, F., Peterson, M., Rhodes, J. & Nagel, R. 2015. Development of an automated ontology generator for analyzing customer concerns. In *IEEE Systems and Information Engineering Design Symposium*, 85–90.

Davies, R. 2015. *Smart Factory Market*. Briefing September 2015, PE 568.337, European Parliament. Members' Research Service.

de Moura Leite, A. F. C., Canciglieri, M. B., Szejka, A. L. & Canciglieri Jr, O. 2017. The reference view for semantic interoperability in integrated product development process: the conceptual structure for injecting thin walled plastic products. *Journal of Industrial Information Integration* **7**(Supplement C), 13–23.

Disi, E. O. and Zualkernan, I. A. 2009. Compliance-oriented process maps and SLA ontology to facilitate Six Sigma define phase for SLA compliance processes. In *IEEE International Conference on Management and Service Science*, 1–4.

Dobrev, M., Gocheva, D. & Batchkova, I. 2008. An ontological approach for planning and scheduling in primary steel production. In *IEEE International Conference on Intelligent Systems*, 6.14–6.19.

Drath, R. & Horch, A. 2014. Industrie 4.0: hit or hype? [industry forum]. *IEEE Industrial Electronics Magazine* **8**(2), 56–58.

Du, R., Li, Y., Shang, F. & Wu, Y. 2010. Study on ontology-based knowledge construction of petroleum exploitation domain. In *IEEE International Conference on Artificial Intelligence and Computational Intelligence*, 42–46.

Engel, G., Greiner, T. & Seifert, S. 2018. Ontology-assisted engineering of cyber-physical production systems in the field of process technology. *IEEE Transactions on Industrial Informatics* **14**(6), 2792–2802.

Fang, Y., Jiaming, Z., Yaohui, L. & Mei, G. 2016. Semantic description and link construction of smart tourism linked data based on big data. In *IEEE International Conference on Cloud Computing and Big Data Analysis*, 32–36.

Feng, L., Chen, G., Chen, C., Chen, L. & Peng, J. 2018. Ontology faults diagnosis model for the hazardous chemical storage device. In *IEEE International Conference on Cognitive Informatics and Cognitive Computing*, 269–274.

Fiorini, S. R., Bermejo-Alonso, J., Goncalves, P., Pignaton de Freitas, E., Olivares Alarcos, A., Olszewska, J. I., Prestes, E., Schlenoff, C., Ragavan, S. V., Redfield, S., Spencer, B. & Li, H. 2017. A suite of ontologies for robotics and automation. *IEEE Robotics and Automation Magazine* **24**(1), 8–11.

Flatt, H., Koch, N., Rocker, C., Gunter, A. & Jasperneite, J. 2015. A context-aware assistance system for maintenance applications in smart factories based on augmented reality and indoor localization. In *IEEE Conference on Emerging Technologies and Factory Automation (ETFA)*, 1–4.

Grangel-Gonzalez, I., Halilaj, L., Auer, S., Lohmann, S., Lange, C. & Collarana, D. 2016. An RDF-based approach for implementing Industry 4.0 components with administration shells. In *IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 1–8.

Guo, R. & Wu, J. 2012. Design and implementation of domain ontology-based oilfield non-metallic pipe information retrieval system. In *IEEE International Conference on Computer Science and Information Processing*, 813–816.

Haidegger, T., Galambos, P. & Rudas, I. 2019. Robotics 4.0 - Are we there yet? In *IEEE International Symposium on Intelligent Engineering Systems*, 1–7.

Hassani, A., Medvedev, A., Haghighi, P. D., Ling, S., Indrawan-Santiago, M., Zaslavsky, A. & Jayaraman, P. P. 2018. Context-as-a-Service Platform: exchange and share context in an IoT ecosystem. In *IEEE International Conference on Pervasive Computing and Communications Workshops*, 385–390.

Haupert, J., Bergweiler, S., Poller, P. & Hauck, C. 2014. IRAR: smart intention recognition and action recommendation for cyber-physical industry environments. In *IEEE International Conference on Intelligent Environments*, 124–131.

Hermann, M., Pentek, T. & Otto, B. 2014. Industry 4.0: The New Industrial Revolution How Europe will Succeed. *Technical report. Think Act*.

Hermann, M., Pentek, T. & Otto, B. 2016. Design principles for industrie 4.0 scenarios. In *IEEE Hawaii International Conference on System Sciences*, 3928–3937.

Hildebrandt, C., Scholz, A., Fay, A., Schroder, T., Hadlich, T., Diedrich, C., Dubovy, M., Eck, C. & Wiegand, R. 2017. Semantic modeling for collaboration and cooperation of systems in the production domain. In *IEEE International Conference on Emerging Technologies and Factory Automation*, 1–8.

Hooi, Y. K., Hassan, M. F. & Ci, T. 2012. Interoperation of elements in process safety management via ontology-oriented architecture. In *IEEE International Conference on Computer and Information Science*, 995–999.

Hoppe, T., Eisenmann, H., Viehl, A. & Bringmann, O. 2017. Shifting from data handling to knowledge engineering in aerospace industry. In *IEEE International Systems Engineering Symposium*, 1–6.

IEEE-SA 2015. *IEEE Standard Ontologies for Robotics and Automation*. Available at: https://standards.ieee.org/standard/1872-2015.html [Accessed 22-October-2019].

Ivaschenko, A., Khorina, A. & Sitnikov, P. 2018. Accented visualization by augmented reality for smart manufacturing aplications. In *IEEE Industrial Cyber-Physical Systems*, 519–522.

Ivezic, N. & Ljubicic, M. 2016. Towards a road-mapping ontology for open innovation in smart manufacturing. In *IEEE International Conference on Collaboration Technologies and Systems*, 77–80.

Izhar, T. A. T. & Apduhan, B. O. 2017. Configuring the relationships of organizational goals based on ontology framework. In *IEEE SmartWorld, Ubiquitous Intelligence and Computing, Advanced and Trusted Computed, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People and Smart City Innovation*, 1–6.

Jayarathna, H. M. H. R. & Hettige, B. 2013. Agricom: a communication platform for agriculture sector. In *IEEE International Conference on Industrial and Information Systems*, 439–444.

Jiang, P., Peng, Y. & Mair, Q. 2004. Concept mining for distributed alliance in multi-agent based virtual enterprises. In *IEEE International Conference on Cybernetics and Intelligent Systems*, 448–453.

Jirkovsky, V., Obitko, M. & Marik, V. 2017. Understanding data heterogeneity in the context of cyber-physical systems integration. *IEEE Transactions on Industrial Informatics* **13**(2), 660–667.

Jost, J., Kirks, T. & Mattig, B. 2017. Multi-agent systems for decentralized control and adaptive interaction between humans and machines for industrial environments. In *IEEE International Conference on System Engineering and Technology*, 95–100.

Kannengiesser, U. & Muller, H. 2013. Towards agent-based smart factories: a subject-oriented modeling approach. In *IEEE/WIC/ACM International Joint Conferences on Web Intelligence (WI) and Intelligent Agent Technologies (IAT)*, 83–86.

Kao, Y.-C. & Chen, M.-S. An agent-based distributed smart machine tool service system. In *IEEE International Symposium on Computer, Communication, Control and Automation*, 41–44.

Kattepur, A., Dey, S. & Balamuralidhar, P. 2018. Knowledge based hierarchical decomposition of Industry 4.0 robotic automation tasks. In *Annual Conference of the IEEE Industrial Electronics Society*, 3665–3672.

Keller, R. M. 2016. Ontologies for aviation data management. In *IEEE/AIAA Digital Avionics Systems Conference*, 1–9.

Kim, S. & Lee, K. 2013. Design of the integrated monitoring framework based on ontology for analyzing the customer feedback. In *IEEE International Conference on Information Science and Applications*, 1–4.

Koetter, F., Blohm, M., Kochanowski, M., Goetzer, J., Graziotin, D. & Wagner, S. 2019. Motivations, classification and model trial of conversational agents for insurance companies. In *International Conference on Agents and Artificial Intelligence*, 19–30.

Koppensteiner, G., Hametner, R., Paris, R., Passani, A. M. & Merdan, M. 2011. Knowledge driven mobile robots applied in the disassembly domain. In *IEEE International Conference on Automation, Robotics and Applications*, 52–56.

Kossmann, M., Gillies, A., Odeh, M. & Watts, S. 2009. Ontology-driven requirements engineering with reference to the aerospace industry. In *IEEE International Conference on the Applications of Digital Information and Web Technologies*, 95–103.

Kourtis, G., Kavakli, E. & Sakellariou, R. 2019. A rule-based approach founded on description logics for Industry 4.0 smart factories. *IEEE Transactions on Industrial Informatics* **15**(9), 4888–4899.

Lee, J., Bagheri, B. & Kao, H.-A. 2015. A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters* **3**(Supplement C), 18–23.

Lehmann, J., Heussner, A., Shamiyeh, M. & Ziemer, S. 2018. Extracting and modeling knowledge about aviation for multilingual semantic applications in Industry 4.0. In *IEEE International Conference on Enterprise Systems*, 56–60.

Li, P. & Niggemann, O. 2018. A data provenance based architecture to enhance the reliability of data analysis for Industry 4.0. In *IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 1375–1382.

Liandong, Z. & Qifeng, W. 2009. Knowledge discovery and modeling approach for manufacturing enterprises. In *IEEE International Symposium on Intelligent Information Technology Application*, 291–294.

Liao, K., Liu, Q. & Zhao, X. 2009. Ontology-based model of mobile knowledge service for the inspection of construction project. In *IEEE International Conference on Management and Service Science*, 1–5.

Liu, J., Wang, Y., Morris, J. & Kristiansen, H. 2005a. Development of ontology for the anisotropic conductive adhesive interconnect technology in electronics applications. In *IEEE International Symposium on Advanced Packaging Materials: Processes, Properties and Interfaces*, 193–208.

Liu, J., Wang, Y., Morris, J. & Kristiansen, H. 2005b. Ontology for the anisotropic conductive adhesive interconnect technology for electronics packaging applications. In *IEEE Conference on High Density Microsystem Design and Packaging and Component Failure Analysis*, 1–17.

Lorenzi, F., Loh, S. & Abel, M. 2011. PersonalTour: a recommender system for travel packages. In *IEEE/WIC/ACM International Conferences on Web Intelligence and Intelligent Agent Technology*, 333–336.

MacDonald, P. 2016. Future trends in engineering: global urbanisation and the fourth industrial revolution. http://www.engineersjournal.ie/2016/06/14/ [Accessed 6-October-2017].

Macia-Perez, F., Gilart-Iglesias, V., Ferrandiz-Colmeiro, A., Berna-Martinez, J. V. & Gea-Martinez, J. 2009. Semantic-driven manufacturing process management automation. In *IEEE Conference on Emerging Technologies and Factory Automation (ETFA)*, 1–8.

Markets and Markets. 2016. *Industry 4.0: Digitalisation for Productivity and Growth*. Technical report, Report Code: SE 3068. Markets and Markets.

Martin-Montes, A., Burbano, M. & Leon, C. 2017. Efficient services in the Industry 4.0 and intelligent management network. In *IEEE International Symposium on Industrial Electronics*, 1495–1500.

Matzler, S. & Wollschlaeger, M. 2017. Interchange format for the generation of functional elements forindustrie 4.0 components. In *Annual Conference of the IEEE Industrial Electronics Society*, 5453–5459.

Merdan, M., Koppensteiner, G., Zoitl, A. & Hegny, I. 2008. Intelligent-agent based approach for assembly automation. In *IEEE Conference on Soft Computing in Industrial Applications*, 13–19.

Meridou, D. T., Kapsalis, A. P., Papadopoulou, M.-E. C., Karamanis, E. G., Patrikakis, C. Z., Venieris, I. S. & Kaklamani, D.-T. I. 2015. An ontology-based smart production management system. *IT Professional* **17**(6), 36–46.

Mozzaquatro, B. A., Melo, R., Agostinho, C. & Jardim-Goncalves, R. 2016. An ontology-based security framework for decision-making in industrial systems. In *IEEE International Conference on Model-Driven Engineering and Software Development*, 779–788.

Muller, T., Hagenmeyer, V., Schmidt, A., Scholz, S. & Elkaseer, A. 2018. A knowledge-based decision support system for micro and nano manufacturing process chains. In *Euromicro Conference on Software Engineering and Advanced Applications*, 314–320.

Natarajan, S., Ghosh, K. & Srinivasan, R. 2011. An evaluation of a hierarchical multi agent based process monitoring system for chemical plants. In *IEEE International Conference on Networking, Sensing and Control*, 151–156.

Nilsson, J. & Sandin, F. 2018. Semantic interoperability in Industry 4.0: survey of recent developments and outlook. In *IEEE International Conference on Industrial Informatics*, 127–132.

Nordrum, A. & Clark, K. 2017. Everything you need to know about 5G. *IEEE Spectrum*.

Olszewska, J. I. 2011. Spatio-temporal visual ontology. In *EPSRC Workshop on Vision and Language (VL)*.

Olszewska, J. I. 2017. Clock-model-assisted agent's spatial navigation. In *International Conference on Agents and ArtificialIntelligence*, 687–692.

Olszewska, J. I. & Allison, A. K. 2018. ODYSSEY: Software development life cycle ontology. In *Proceedings of the International Conference on Knowledge Engineering and Ontology Development*, 303–311.

Olszewska, J. I., Barreto, M., Bermejo-Alonso, J., Carbonera, J., Chibani, A., Fiorini, S., Goncalves, P., Habib, M., Khamis, A., Olivares, A., Freitas, E. P., Prestes, E., Ragavan, S. V., Redfield, Sanz, R., Spencer, B. & Li, H. 2017. Ontology for autonomous robotics. In *IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, 189–194.

Olszewska, J. I., Houghtaling, M., Goncalves, P. J.S., Fabiano, N., Haidegger, T., Carbonera, J. L., Patterson, W. R., Ragavan, S. V., Fiorini, S. R. & Prestes, E. 2019. Robotic ontological standard development life cycle in action. *Journal of Intelligent and Robotic Systems*, 1–20.

Persson, C. & Wallin, E. O. 2017. Engineering and business implications of ontologies: a proposal for a minimum viable ontology. In *IEEE Conference on Automation Science and Engineering*, 864–869.

Phutthisathian, A., Maneerat, N., Varakulsiripunth, R., Takahashi, K. & Kato, Y. 2013. An ontology-based multi agent automotive parts transportation management system. In *IEEE Region 10 Humanitarian Technology Conference*, 96–99.

Prestes, E., Carbonera, J. L., Fiorini, S. R., Jorge, V. A. M., Abel, M., Madhavan, R., Locoro, A., Goncalves, P., Barreto, M. E., Habib, M., Chibani, A., Gerard, S., Amirat, Y. & Schlenoff, C. 2013. Towards a core ontology for robotics and automation. *Robotics and Autonomous Systems* **61**(11), 1193–1204.

Rappaport, T. S., Sun, S., Mayzus, R., Zhao, H., Azar, Y., Wang, K., Wong, G. N., Schulz, J. K. & Samimi, M. 2013. Millimiter wave mobile communications for 5G cellular: it will work! *IEEE Access* **1**, 335–349.

Ray, P. P. 2016. Internet of robotics things: concept, technologies, and challenges. *IEEE Access* **4**, 9489–9500.

Rosen, R., von Wichert, G., Lo, G. & Bettenhausen, K. D. 2015. About the importance of autonomy and digital twins for the future of manufacturing. *IFAC Symposium on Information Control Problems in Manufacturing* **48**(3), 567–572.

Saidur, R. 2010. A review on electrical motors energy use and energy savings. *Renewable and Sustainable Energy Reviews* **14**(3), 877–898.

Salminen, V. & Pillai, B. 2007. Interoperability requirement challenges: future trends. In *IEEE International Symposium on Collaborative Technologies and Systems*, 265–270.

Santos, G., Silva, F., Teixeira, B., Vale, Z. & Pinto, T. 2018. Power systems simulation using ontologies to enable the interoperability of multi-agent systems. In *IEEE Power Systems Computation Conference*, 1–7.

Smirnov, A., Sandkuhl, K. & Shilov, N. 2010. SOA-based product knowledge management for collaborative engineering in virtual enterprises. In *IEEE International Technology Management Conference*, 1–8.

Sorli, M., Mendikoa, I., Perez, J., Soares, A., Urosevic, L., Stokic, D., Moreira, J. & Corvacho, H. 2006. Knowledge-based collaboration in construction industry. In *IEEE International Technology Management Conference*, 1–8.

Tang, H., Li, D., Wang, S. & Dong, Z. 2018. CASOA: an architecture for agent-based manufacturing system in the context of Industry 4.0. *IEEE Access* **6**, 12746–12754.

Teixeira, B., Silva, F., Pinto, T., Santos, G., Praca, I. & Vale, Z. 2017. TOOCC: enabling heterogeneous systems interoperability in the study of energy systems. In *IEEE Power and Energy Society General Meeting*, 1–5.

Veera Ragavan, S. K. & Shanmugavel, M. 2016. Engineering cyber-physical systems - mechatronics wine in new bottles? In *IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, 1–5.

Vinoth, P. & Sankar, P. 2016. Bringing intelligent inferences through a semantic structure markup system with the support of chemical ontologies. In *IEEE International Conference on Advances in Computer Applications*, 60–65.

Vukmirovic, M., Szymczak, M., Ganzha, M. & Paprzycki, M. 2006. Utilizing ontologies in an agent-based airline ticket auctioning system. In *IEEE International Conference on Information Technology Interfaces*, 385–390.

Wally, B., Huemer, C. & Mazak, A. 2017. Aligning business services with production services: the case of REA and ISA-95. In *IEEE Conference on Service-Oriented Computing and Applications*, 9–17.

Wan, J., Chen, B., Imran, M., Tao, F., Li, D., Liu, C. & Ahmad, S. 2018a. Toward dynamic resources management for IoT-based manufacturing. *IEEE Communications Magazine* **56**(2), 52–59.

Wan, J., Yin, B., Li, D., Celesti, A., Tao, F. & Hua, Q. 2018b. An ontology-based resource reconfiguration method for manufacturing cyber-physical systems. *IEEE/ASME Transactions on Mechatronics* **23**(6), 2537–2546.

Wan, J., Tang, S., Li, D., Imran, M., Zhang, C., Liu, C. & Pang, Z. 2019. Reconfigurable smart factory for drug packing in healthcare Industry 4.0. *IEEE Transactions on Industrial Informatics* **15**(1), 507–516.

Wang, G., Wong, T. N. & Wang, X. H. 2010. A negotiation protocol to support agent argumentation and ontology interoperability in MAS-based virtual enterprises. In *IEEE International Conference on Information Technology: New Generations*, 448–453.

Wang, J., Sun, Y., Zhang, W., Thomas, I., Duan, S. & Shi, Y. 2016. Large-scale online multitask learning and decision making for flexible manufacturing. *IEEE Transactions on Industrial Informatics* **12**(6), 2139–2147.

Wiesner, A., Saxena, A. & Marquardt, W. 2010. An ontology-based environment for effective collaborative and concurrent process engineering. In *IEEE International Conference on Industrial Engineering and Engineering Management*, 2518–2522.

Wollschlaeger, M., Sauter, T. & Jasperneite, J. 2017. The future of industrial communication: automation networks in the era of the Internet of Things and Industry 4.0. *IEEE Industrial Electronics Magazine* **11**(1), 17–27.

Xie, C., Cai, H., Xu, L., Jiang, L. & Bu, F. 2017. Linked semantic model for information resource service towards cloud manufacturing. *IEEE Transactions on Industrial Informatics* **13**(6), 3338–3349.

Xu, X. 2012. From cloud computing to cloud manufacturing. *Robotics and Computer-Integrated Manufacturing* **28**(1), 75–86.

Xu, X. & Hua, Q. 2017. Industrial big data analysis in smart factory: current status and research strategies. *IEEE Access* **5**, 17543–17551.

Xue, X. & Chang, J. 2012. The research on context-aware-based intelligent service system for miners. In *IEEE International Conference on Services Computing*, 478–485.

Yusupova, N., Smetanina, O., Agadullina, A. & Rassadnikova, E. 2017. The development of ontologies to support the decisions in production systems management. In *Russia and Pacific Conference on Computer Technology and Applications*, IEEE, 188–193.

Zhang, C., Zhou, G. & Lu, Q. 2017. Decision support oriented ontological modeling of product knowledge. In *IEEE Information Technology, Networking, Electronic and Automation Control Conference*, 39–43.

Zhang, J., Ahmad, B., Vera, D. & Harrison, R. 2018. Automatic data representation analysis for reconfigurable systems integration. In *IEEE International Conference on Industrial Informatics*, 1033–1038.

Zhang, Y., Li, L., Nicho, J., Ripperger, M., Fumagalli, A. & Veeraraghavan, M. 2019. Gilbreth 2.0: an industrial cloud robotics pick-and-sort application. In *IEEE International Conference on Robotic Computing*, 38–45.

Zheng, X., Martin, P., Brohman, K. & Xu, L. D. 2014. Cloud service negotiation in Internet of Things environment: a mixed approach. *IEEE Transactions on Industrial Informatics* **10**(2), 1506–1515.